Comparative Analysis of Traffic Congestion Prediction Models for Cellular Mobile Macrocells

Aliyu Ozovehe, Okpo U. Okereke, Anene E. Chibuzo, and Abraham U. Usman

***Abstract*—Traffic congestion prediction is a non-linear process that involves obtaining valuable information from a set of traffic data and linear models cannot be applied because of the dynamics of combined voice and data traffic on one radio channel of GSM/GPRS access network. However, non-linear problems can easily be modeled using Artificial Intelligent (AI) techniques such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). In this work, three types of ANN and an ANFIS models are trained based on busy hour (BH) traffic measurement data taken from some GSM/GPRS sites in Abuja. The models were then used to predict traffic congestion for some macrocells and their accuracy are compared using four statistical indices. It was observed that Group Method of Data Handling *(GMDH)* model which is one of the ANN models has the best fit and predict better than ANFIS and the other two ANN models. The GMDH model is found to offer improved prediction results in terms of increasing the R^2 by 20% and reducing *RMSE* by 60% over ANFIS, the closest model to the GMDH in term of prediction accuracy.**

***Index Terms*—Artificial Intelligent Network; Quality of Service; Busy Hour Traffic and Traffic Congestion.**

I. INTRODUCTION

The GSM service providers in Nigeria have not been able to satisfy Quality of Service (QoS) as a result of network congestion [1] and there is dire need for improved QoS in mobile communication services by providing useful tools for predicting BH traffic congestion which is essential for proper network planning and optimization.

The traffic prediction modeling is a special case of the Box-Jenkins' auto-regressive integrated moving average (ARIMA) models in their framework. However, it is difficult to predict mixed traffic in GSM/GPRS network with ARIMA models because of the bursty nature of the traffic sources and the effects of high-speed channels that characterized the network. Experimental results have shown that the artificial intelligence (AI) techniques are superior to traditional regression or auto-regression techniques as tools for traffic prediction.

This work explored Multiple Layer Perceptron Neural Network (MLPNN), Radial Basis Function Neural Network (RBFNN), Group Method of Data Handling Polynomial Neural Network *(GMDH-PNN)* and ANFIS models that have found application in traffic prediction [2] – [7]. The aim is to train the computational intelligent techniques for planning and optimization of GSMGPRS macrocell using two years' traffic measurement data as a case study. Performances of the models were determined and recommendations made for their applicability in the study area.

II. LITERATURE REVIEW

Basically, ANNs are mostly used for modeling nonlinear statistical data and they mimic the working of neural networks of human brains. Fig. 1 shows a simple neuron model and (1) relates the input to the output of the model.

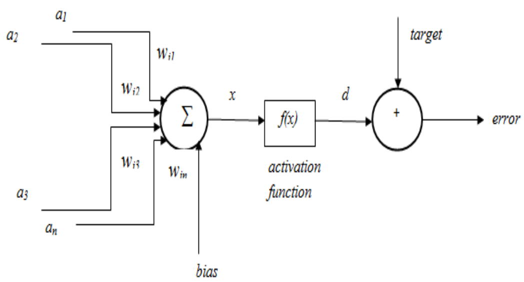

Fig. 1. A common model for neuron

It is obvious from Fig. 1 that the neuron is a processing element that takes a number of inputs, a_1, $a_2 \dots a_n$, weight them with

weights, w_1, $w_2 \dots . w_n$, sums them up together with a bias parameter, $bias$, to get x. x is then processed by the activation function, $f(u)$ and the neuron output error, e, is calculated by subtracting the output, d, from the target value, t, as in (1):

$$e = t - d \quad (1)$$

The essence of neuron model is to minimize the output error, e, according to some optimization criteria to improve goodness of fit.

All the neurons in NNs are trained using a block of inputs and outputs set of data in order for the NNs to have knowledge about the problem. The training can be classified into two, supervised and un-supervised training. The former needs pre-defined set of training data that reflect the network behaviour. The network target is already known and it is compared to the output when the input is applied to the network. The learning rule modifies w_1, $w_2 . w_n$, and $bias$ so that the outputs are closer to the target [8].

Published on June 30, 2018.
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However, $w_1, w_2 . w_n$, and $bias$ parameters are updated solely with inputs data in unsupervised training.

A. *Review Stage Multilayer Perceptron Neural Network (MLPNN)*

MLPNN is an extension of the neuron model and connections can only be unidirectional in the network. Neurons in proceeding layer can only be linked to neurons in the successive layer and the no loops in MLPNN architecture means computation can take place uniformly from input neurons to output neurons [9]. MLPNN has three layers of neurons in its simplest form as shown in Fig. 2 and uses sigmoid activation function in hidden and output layers for supervised learning algorithm that calculate the change in network weights commonly referred to as back-propagation.

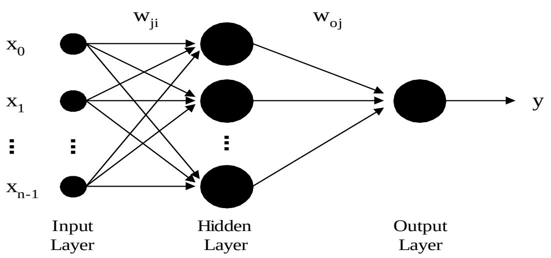

Fig. 2. Simple MLPNN architecture

Thus, MLP network output can be expressed as in (2).

$$y = \frac{\sum_{j=0}^{M} (w_{0j} (F_h (\sum_{i=0}^{N} w_{ji} x_i)))}{F_0^{-1}} \tag{2}$$

The training process minimizes the mean square error *(MSE)* by regulating the $w_1, w_2 \ldots . w_n$ using a block set of data as given in (3).

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{3}$$

where y_i is the measured output value and $\hat{y}_i$ is the predicted output of the network, while N is the sampling numbers.

MLPNN of many layers can easily be designed, [10] has shown that only one hidden layer is necessary to get good result from the network if sigmoid activation function is used.

B. *Radial Basis Function Neural Network (RBFNN)*

RBFNN is an MLPNN network that uses radial basis function as an activation function in the hidden layer. Fig. 3 shows the generalized RBFNN.

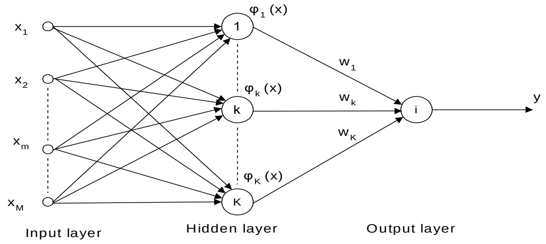

Fig. 3. *Simple RBFNN configuration*

Input into RBFNN is usually modeled as given by (4):

$$x \in R^n \tag{4}$$

where R is a real numbers.

The RBFNN output as a non-vector function can be expressed as in (5):

$$\varphi(x) = \sum_{i=1}^{N} a_i \rho(\|x - c_i\|) \tag{5}$$

RBFNN depends exclusively on length of interval between centre vectors c_i and its norm is taken as Euclidean distance which becomes Gaussian basis function when

$$\lim_{\|x\| \to \infty} \rho(\|x - c_i\|) = 0$$

Use is made of a_i, c_i and ρ parameters for optimal fit between RBFNN output and the data.

RBFNN networks are trained by properly chosen the centre vectors c_i and then use w_i to fits a linear model with respect to some objective (least squares) function. Back propagation step may be performed for optimal a_i, c_i and ρ parameters.

C. *Group Method of Data Handling Polynomial Neural Network (GMDH-PNN) Model*

GMDH-PNN was developed as a model for obtaining high order input- output relationship in time-series problems by identifying non-linear relationships between inputs and outputs data [11]. GMDH is an inductive unidirectional polynomial neural network that is made of large number of layers and each layer contains many neurons. All neurons in GMDH shell have two inputs and one output as shown in Fig. 4.

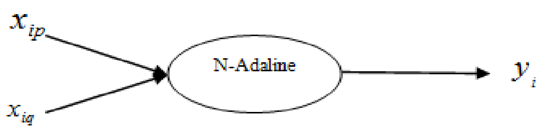

Fig. 4. A Single GMDH Neuron Model

GMDH neuron model can be expressed mathematically as a second order polynomial network (PNN) model and the most popular function used in GMDH is the Kolmogorov-Gabor polynomial with base function as in (6).

DOI: http://dx.doi.org/10.24018/ejers.2018.3.6.767

$$y_i = f(x_{ip}, x_{iq}) = a_0 + a_1 x_{ip} + a_2 x_{iq} + a_3 x_{ip} x_{iq} + a_4 x_{ip}^2 + a_5 x_{iq}^2 \quad (6)$$

The function f is equipped with six x factor estimating $\{(x_{ip}, x_{iq}), i = 1,2,3,...N\}$ system and optimal output of $\{(y_i), i = 1,2,3,...N\}$ for all dependent two-variable samples [12].

Each term of Kolmogorov-Gabor polynomial contributes differently and the GMDH network removes the terms that do not contribute significantly layer by layer using self-organizing arithmetic. The goal of modeling can be reached if the function f is planned according to minimum squares error as shown as in (7).

$$Min \sum_{k=1}^{N} [(f(x_{ip}, x_{iq}) - y_i)^2] \quad (7)$$

Application of ANNs to traffic prediction by [1] – [2], [7] and [13] – [18] showed that MLPNN, RBFNN and GMDH-PNN can predict traffic with very high accuracy.

D. *Adaptive Neuro-Fuzzy Inference Systems (ANFIS)*

ANFIS utilizes the learning ability, adaptability and knowledge discovery of neural networks and fuzzy systems to represent knowledge and figure out inaccurate information [19]. The ANFIS used in this work is a first order Takagi-Sugeno-Kang (TSK) that has inputs, x and y and an output $f(x, y)$ as shown in Fig. 5.

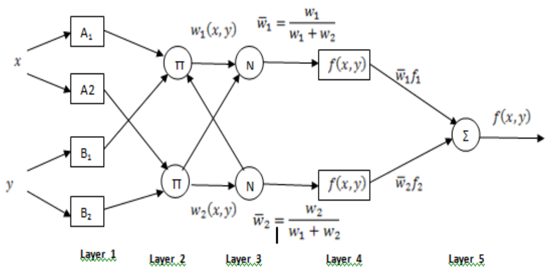

Fig. 5. Simple Configuration of ANFIS

The logic behind the working of TSK inference system can be stated as:

If x is A_i and y is B_i,
THEN fi = $p_i x + q_i y + r_i$

A_i and B_i represents linguistic labels for the input x and y respectively and f_i stands for adaptive linear function of the system.

Layer 1 inputs are fuzzified in this layer by using the membership functions whose parameters are adaptable. The parameters of the MFs are known as antecedent parameters. Fig. 6 shows the most common membership function which is basically a Gaussian bell function.

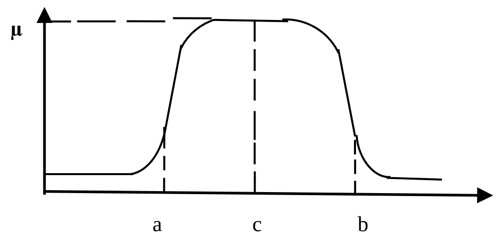

Fig. 6. Bell membership function

The bell function is expressed as in (8):

$$\mu_{yi}(\hat{y}) = \frac{1}{1 + \left[\frac{x - c_i}{a_i}\right]^{2b_i}} \quad (8)$$

where a, b and c are antecedent parameters.

Layer 2 is a hidden layer with fixed nodes that perform the rule of firing strength as given in (9).

$$w_i^n = \prod_{i=1}^{n} \mu_{Ai}(x_i) \mu_{Bi}(y_i) \quad (9)$$

Layer 3 this layer produces an output called normalized firing strength of each rule according to (10).

$$\overline{w_i} = \frac{w_i}{\sum_{j=1}^{2} w_j} \quad (10)$$

Layer 4 is an adaptive node where every node is a linear function of the inputs with some adaptive gains and constant parameters. Each node has a function given in (11).

$$\overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \quad (11)$$

where, p_i, q_i and r_i are referred to as consequent parameters and use is made of least-squares (LS) method in practice to get their optimal values.

Layer 5 defuzzification is performed in this layer to generate a crisp output for the systems as expressed in (12).

$$f(x, y) = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (12)$$

note that $\overline{w_i} f_i$, is layer 4 output.

To estimate the parameters of membership function, ANFIS is trained using either back propagation or least squares estimation and back-propagation.

III. METHODOLOGY

The experimental setup for collecting and processing the traffic data used in this work is shown in Fig. 7. The setup comprises of base station subsystem (BSS) and network subsystem (NSS) connected to standalone system called network management system (NMS) [1].

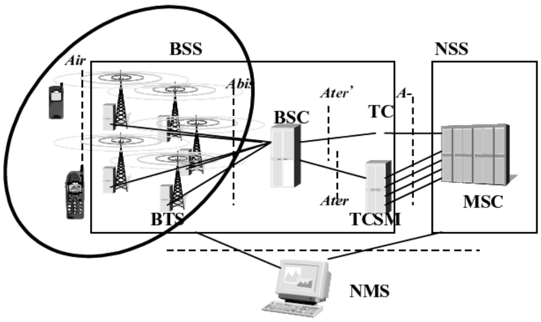

Fig. 7. System for Collecting Data

NMS is the functional entity from which the service provider monitors and controls the entire network. The data used in this work was extracted from the NMS with the help of Ericsson Business intelligent (BI) tools installed on the standalone computer and exported to Microsoft Excel environment and part of the processed data for CELL01 is shown in Table I.

TABLE I: TRAFFIC DATA FOR CELL01

CELL01 DATA		
CSSR	TRAFFIC	TCH CONG
57.92	29.88	2.67
56.9	30.73	2.98
58.71	23.73	3.01
42.35	17.75	3.9
46	19.74	3.97
46.34	17.54	5.12
47.26	19.31	7.73
48.62	19.75	8.84
…	…	…
…	…	…
65.8	18.87	32.1

To develop a good prediction model for the congestion, the selection of the input variables must be closely associated with the TCH congestion values and there must be a strong linear correlation between the traffic parameters (CSSR, HOSR, DCR, SDCCH congestion and busy hour BH traffic) and TCH congestion. Correlation test showed that traffic channel (TCH) congestion depend only on call setup success rate (CSSR) and BH traffic at cell level. An average correlation coefficient value of 0.9 was observed between TCH congestion and CSSR while 0.6 was observed between TCH congestion and BH traffic [1].

To fit BH traffic versus TCH congestion pairs for each Cell:

- *newff* function of MATLAB was used to create an MLPNN 2-3-1 (two inputs, three hidden layer and one input). MATLAB *rand* was used to set a random seed ('seed', 447944968) to avoid randomness experienced in each run of the MATLAB program. The network was trained with LMA in order to avoid over fitting and early stopping.
- An optimal RBFNN performance was achieved when 0.5 spread constant is used as default data length to fit BH traffic/CSSR versus TCH congestion pairs for each Cell.
- For standard GMDH-PNN model, BH traffic/CSSR and TCH congestion pairs of each cell was fit into GDMH shell which create a second order polynomial network. The traffic data was imported in to GMDH shell environment in XLS format to train and validate the model for predicting the busy hour congestion of the cell using k-fold cross-validation to split the whole dataset into ratio 40:60 for training and testing respectively.
- For optimal performance of ANFIS model 25 was used as number of fuzzy MF per input, Bell membership function (MF) was specified as the type of fuzzy MF and 300 was taken the number of epochs [20] before the training.

Table II shows the various parameters used for the four models.

TABLE II: PARAMETERS OF THE MODELS

Parameter	Value
No. of MLP Hidden Layer 1	1
No. of MLP Hidden Layer 2	3
No. of epochs	300
No. of RBF neurons	Default length of data
RBF's spread	0.5
RBF's error goal	0.01
GMDH's training	k-1
No. of ANFIS MF	25

Four standard statistical performance evaluation criteria- mean absolute error (*MAE*), standard deviation (SD) and root mean square error (RMSE) and R-Square (R^2) values as in (13 –16) were used to measure the performances of these models.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} E_i \tag{13}$$

where $E_i = |y_i - \hat{y}_i|$ and N is the sampling numbers.

MAE measures how close the predictions are to the measured congestion.

$$SD = \sqrt{\frac{1}{N-1}\left(\sum_{i=1}^{N} E_i^2 - N.\mu^2\right)} \tag{14}$$

SD quantifies the total deviation in a set of samples data and a low value depicts that the samples data are close to the mean of the set.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{15}$$

RMSE aggregates the amount of errors in predictions and the lower the value the higher the accuracy of the prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{16}$$

where, $\bar{y}_i$ is input data (congestion) mean

R^2 shows the closeness of the predicted values to the fitted regression line.

IV. Result and Discussion

The traffic measurement data was split into parts: 40% training and 60% testing for the four models. Plots for the training errors, validation errors and errors test performance of the four CELLs are shown in Fig 8 – 11 while Tables III–IV present the numerical value of μ, σ, RMSE and R^2 for the four CELLs and the models.

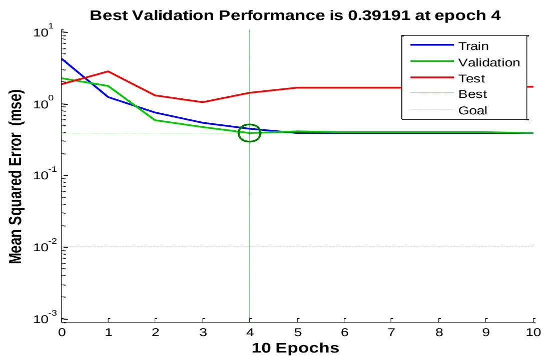

Fig. 8: CELL1 training, validation and errors test

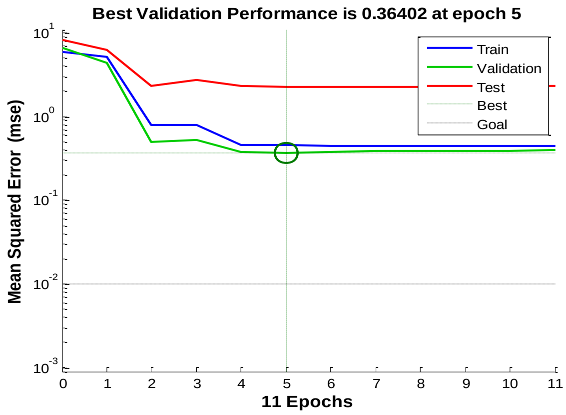

Fig. 9: CELL2 training, validation and test errors test

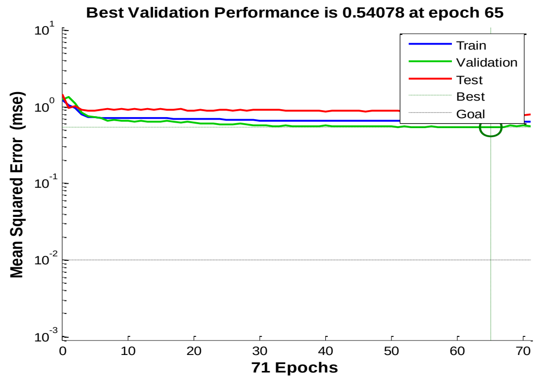

Fig. 10. CELL3 training, validation and errors test

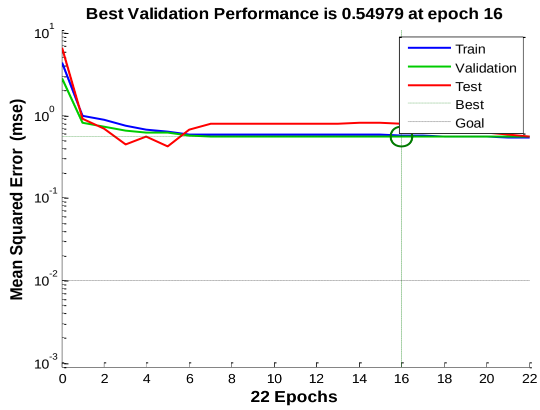

Fig. 11. CELL4 training, validation and errors test

TABLE III: MAE Performance of the Models

Site	MLP	RBF	ANFIS	GDMH
CELL01	13.53	6.79	4.22	2.65
CELL02	7.12	0.33	4.65	3.83
CELL03	18.42	0.39	7.32	0.67
CELL04	10.75	1.68	3.91	2.13
Average	13.15	2.3	5.02	2.32

TABLE IV: *SD* Performance of the Models

Site	MLP	RBF	ANFIS	GDMH
CELL 1	12	12.43	5.69	3.91
CELL 2	7.19	0.26	5.3	4.56
CELL 3	14.29	0.22	8.81	0.94
CELL 4	8.16	1.38	5.07	4.72
Average	11.52	3.52	6.22	3.53

TABLE V: *RMSE* Performance of the Models

Site	MLP	RBF	ANFIS	GDMH
CELL 1	17.96	13.36	7.05	3.91
CELL 2	10.09	0.41	7.04	4.62
CELL 3	23.28	0.44	11.44	0.94
CELL 4	13.47	2.11	6.39	4..77
Average	17.46	4.08	7.98	3.16

TABLE VI: R^2 Performance of the Models

Site	MLP	RBF	ANFIS	GDMH
CELL 1	0.34	-2.62	0.92	1
CELL 2	0.44	0.13	0.7	0.97
CELL 3	0.14	0.44	0.79	1
CELL 4	0.36	-0.04	0.87	1
Average	0.32	-0.61	0.82	0.99

DOI: http://dx.doi.org/10.24018/ejers.2018.3.6.767

Fig. 12 – 13 showed that the analysis of the models performance using MAE, SD, RMSE and R^2.

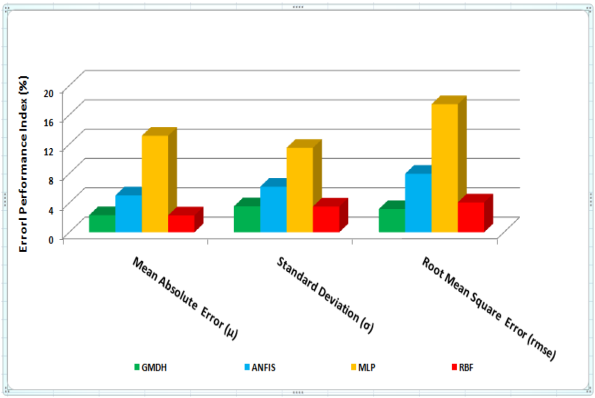

Fig. 12. Average error performance of the four models

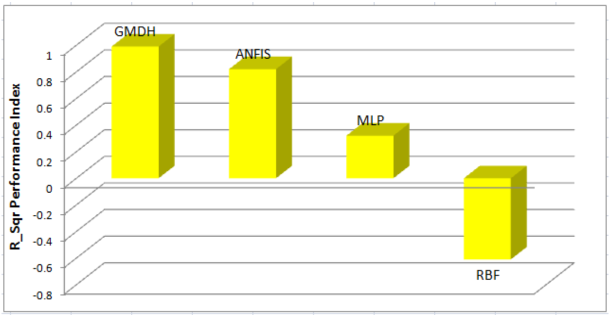

Fig. 13. Average goodness performance of the four models

Fig. 13 showed that GMDH-PNN model has the best performance using the most important statistical measure, R^2. The average R^2 performance of the GMDH-PNN, ANFIS, MLPNN and RBFNN models are 0.99, 0.82, 0.32 and -0.61 respectively.

Using *MAE, SD* and *RMSE* in Fig. 12, the RBFNN model performances compete favorably with GMDH-PNN model. However, RBFNN negative value R^2 makes it an inappropriate model for this prediction when compared to other models.

The *RMSPE* values of MLPNN model is extremely too high in all the Cells when compared with other Models and hence is not good for modeling the data. Also, the ANFIS model performance is next to GMDH-PNN model in term of predictions accuracy while the performance RBFNN model is the worst.

V. Conclusion

GMDH-PNN predicted TCH congestion better than any other models because it produces lower error in terms of *MAE*, *SD*, *RMSE* and higher R^2 between actual and predicted TCH congestion. These suggest the suitability of GMDH-NN for prediction of TCH congestion for effective management of macrocell network resources in cellular mobile.

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